Ecological Modelling 385 (2018) 35–44

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Mapping invasion potential using ensemble modelling. A case study on *Yushania maling* in the Darjeeling Himalayas

Vivek Srivastava[a,*,1], Verena C. Griess[a,1], Hitendra Padalia[b]

[a] Department of Forest Resources Management, Faculty of Forestry, University of British Columbia, Canada
[b] Forestry and Ecology Department, Indian Institute of Remote Sensing, ISRO, Dehradun 248001, India

ARTICLE INFO

Keywords:
Yushania maling
Invasive species
Ensemble model
Maxent
GARP
BIOCLIM

ABSTRACT

Biological invasion is considered the subsequent most important threat to biodiversity after habitat destruction and is documented as a main cause of global biodiversity loss and species extinction. Species distribution models can be used to identify areas that are at risk for invasions by harmful invasive alien species (IAS) if IAS have not yet spread to all suitable habitats. We tested the potential of combining two or more independent but complementary modelling methods to enhance the accuracy of spatial predictions. We used the modelling tools Maxent, GARP and BIOCLIM with presence-only data of the IAS *Yushania maling* (Maling bamboo), from Darjeeling, Himalaya to develop distribution maps. Modelling tools were chosen based on their performance with presence-only data (Area under curve (AUC) > 0.7) as well as their differences in underlying modelling concept and statistics. The models combine occurrence records with topographic, climatic, and vegetative predictors derived from satellite data. By combining the 3 selected models in an ensemble approach we were able to minimize the spatial uncertainty related to suitable habitat prediction for *Yushania maling*. While both GARP and BIOCLIM consistently performed at an AUC > 0.7, both our ensemble model and Maxent performed better with an AUC of 0.95 and 0.94 respectively. Moderately and highly suitable habitats for *Yushania maling* predicted by models correlated well with survey records except for GARP, where we found the model to over-predict suitability outside of the species' known ecological niche. Our findings identify the best modelling approach enhancing overall explanatory power of habitat suitability models. Our findings show that an ensemble approach should be used to ensure appropriate mitigation measures are applied in the appropriate places, enhancing overall effectiveness both ecologically as well as economically. It was shown that *Yushania maling* is indeed a threat to the ecosystems in the region, and while the species' potential habitat may decrease in some areas with climate change, other areas will become more suitable for it.

1. Introduction

The Darjeeling district in the Himalaya region, India, is a hotspot for biodiversity, endemism and micro-diversity. Over past decades, rapid population growth has led to increasing anthropogenic disturbances in the region and a consistent increase in pressure on the environment. The inflating level of anthropogenic activity, a growing ecological susceptibility due to climate change, disturbances and other factors make the area prone to invasions by non-native species. Invasive alien species (IAS) are species that are capable of getting established outside their natural ranges. They commonly show a high potential for spread and can become established outside their historical range, causing – often irreversible - damage to the environment. Biological invasions have led to the extinction of thousands of endemic species in the past few hundred years (Mooney and Drake, 1987) and have homogenized the world's flora and fauna (Hobbs, 2000). In the Darjeeling region, such invasions are causing considerable ecological damage to the native flora and fauna (Sekar, 2012). *Yushania maling* (Gamble) is a native invasive species to the region. The species was previously known as *Arundinaria maling* (Majumdar et al., 1989), in the *Yushania* genus of bamboo in the grass family. Starting in the late 1980ies first occurrences were recorded in India's Darjeeling district (Chi-son and Renvoize, 1989). Since then, the species has been spreading at an alarming rate, damaging the native fauna and flora (Roy et al., 2016) by

Abbreviations: AUC, area under curve; DEM, digital elevation model; EM, ensemble model; IAS, invasive alien species; LULC, land use land cover map; mamsl, meters above mean sea level; NP, national park; ROC, receiver operating characteristic; SDM, species distribution model; WLS, wildlife sanctuary

* Corresponding author.
E-mail addresses: vivek.srivastava@ubc.ca (V. Srivastava), verena.griess@ubc.ca (V.C. Griess), hitendra@iirs.gov.in (H. Padalia).
[1] Forest Sciences Centre, 2424 Main Mall, Vancouver, British Columbia V6T1Z4, Canada.

https://doi.org/10.1016/j.ecolmodel.2018.07.001
Received 14 February 2018; Received in revised form 15 June 2018; Accepted 6 July 2018
Available online 20 July 2018
0304-3800/ © 2018 Elsevier B.V. All rights reserved.

rapidly outcompeting native species (Stapleton, 1997).

The management and mitigation of IAS has been at the center of attention of scientific research for many decades (Elton, 1958). While numerous studies demonstrate the dramatic effect of invaders on recipient ecosystems (Mack et al., 2000), other studies are working towards possible ways to tackle the challenges arising from biological invasions. Guisan and Zimmermann (2000); Scott, (2002) as well as Guisan and Thuiller (2005) for example demonstrate the importance of species distribution modelling (SDM) in general, and describe a variety of methods available for the prediction of a species' potential habitat. Jiménez-Valverde et al., (2011) advocate the role that SDM can play in risk assessment and conservation. Timely information about areas under risk of being invaded can help in devising effective control and eradication strategies, aiding decision making by resources managers, government agencies, and non-government organizations.

One way to identify potential areas of spread of invasive species is through modelling their current distribution (Padalia et al., 2014), followed by species-environment matching for areas outside a species current range. The accuracy and performance of individual SDM varies widely among methods and species (Elith et al., 2006; Marmion et al., 2009). Methods integrating multiple individual models provide robust estimates of potential species' distributions (Araujo and New, 2007; Marmion et al., 2009). Ensemble maps that highlight areas of agreement among model predictions offer a way to reduce the uncertainty of basing management activities on solely one SDM model. The importance of study manifolds taking into account that there are limited related studies in the past.

An increasing availability of spatial data, as well as high resolution bio-climatic data have continuously enhanced the prerequisites needed for successful SDM and assessment of factors affecting the magnitude and extent of a potential invasion. Using such data, Ensemble Models (EM) have the potential to provide more robust estimates of suitable habitat for a given invasive species at a given time (Meller et al., 2014; Poulos et al., 2012), leading to robust SDM. In EM the predictions of a group of base models are combined to generate more accurate composite predictions. Particularly when analysing the risk of IAS that have not yet spread to all suitable habitats the determination of species-environment relationships can be challenging (Stohlgren et al., 2010). In such cases, EM have the potential to highlight areas of agreement among models, using a range of modelling techniques (Araujo and New, 2007; Marmion et al., 2009; Stohlgren et al., 2010).

In recent years, EM methods have been improved in a variety of ways to produce more accurate estimates of species distribution and to facilitate conservation measures. For e.g., Comte (2013) assessed the influence of species non-detection in modelling species distributions with an ensemble consensus approach and compared it with an occupancy model that accounted for species imperfect detection and found consensus models to outperform the occupancy models for the highly detectable species. Forester et al., (2013) integrated two independent-complementary methods, EM and statistical phylogeography and produced robust assessments of climate change impacts on species distributions. Whereas, Meller et al., (2014) evaluated and compared the pre-selection and post-selection consensus approaches in conservation prioritization. Breiner et al., (2015), in addition to introducing fresh approach of using ensembles of small models (ESM) to model the distribution of rare species, tested the approach more comprehensively on a large number of species including a transferability assessment. Recently, Naimi and Araújo (2016) created a R based platform for species distribution modelling, enabling ensembles of models to be fitted and evaluated. The R package can generate ensembles of SDMs and offers variety of options for the evaluation of the produced projections of species potential distributions in space and time. A very recent R package "ecospat" developed by Cola et al., (2017) provide adequate functions to run the very recently proposed ensemble of small models (ESM) approach (Breiner et al., 2016). Further, using the R based package "BIOMOD2" devloped by Thuiller et al., (2016); Gillard et al., (2017) performed ensemble forecasting by using nine different algorithms including: three regression based methods, two classification based and four machine learning methods to forecast current and future potential distribution of three invasive plant taxa.

While it is generally understood that SDM derived using EM can have a stronger explanatory power than SDM from individual models, little is known about both the ideal combination of base models in an EM, and whether or not the benefits of EM shown for well researched cases can also be obtained when working with limited data from specific case study regions, where decision makers are facing pressure to act. In a first step we therefore assess our first hypothesis:

H0,1. Model performance of Maxent, GARP and BIOCLIM is similar to that of EM when using field data for *Yushania maling*.

Successfully deriving an ideal modelling approach using limited real-world data will additionally allow us to investigate a second hypothesis, directly aimed to assist decision makers.

H0,2. The spread of *Yushania maling* is limited. No currently unaffected areas in the region are at risk of being invaded.

By answering this hypothesis areas under risk can be identified and required policies can be developed to ensure timely and appropriate counter measurements are implemented. When it comes to ensuring a longer-term applicability of answer to these two hypotheses it becomes evident that climate change has to be addressed as well. Climate change might impact the distribution and potential habitat of invasive *Yushania maling* and eventually affect the effectiveness of control measures. Therefore to identify the impacts of climate change on potential distribution of *Yushania maling* and to aid the long term IAS management plan, we investigate our third hypothesis.

H0,3. There is no difference in the potential habitat of *Yushania maling* under a changing climate.

2. Methods and material

To answer our hypotheses, occurrence data was collected that, together with additional data on bio climate and other ecological parameters were used to develop an EM. In the following, we will be describing the study area, our approach for collecting data in the field, as well as the approach used for modelling.

2.1. Study area

The study area is located in the Darjeeling Himalayas (Fig. 1), India. The area is located at 87°59′ E - 88°53′ E to 27°14′ N - 26°27′ N and includes the Himalayan parts of Sikkim, Nepal, Bhutan and Bangladesh encompassing an area of 8812 km^2

The region is home to a diverse alpine flora belonging to 60 families and 297 genera covering 60% of all alpine plant families and 10% of all the alpine genera known worldwide (Körner, 1999). The total number of vascular plant species recorded across the region (1400 ± 75 species) is more than double of that recorded for the European Alps, New Zealand Alps and the Rocky Mountains region (600–650 species) (Mark and Adams, 1973; Hadley, 1987; Ozenda, 1995). Remarkably, the Darjeeling Himalayas region is one of smallest regions in terms of geographic area, yet has the highest number of species per km^2.The area covers 3 national parks and 7 wildlife sanctuaries (Singalilia NP, Neora Valley NP, Gorumara NP, Jorepokhri Salamander WLS, Senchal WLS, Mahananda WLS, Chapramari WLS, Pangolakha WLS, Barsay WLS, and Kitam WLS). The area is additionally covering a variety of climatic zones with distinct attributes, leading to a comparably high overall biodiversity. The region is also a source of vast variety of medicinal plants, which are extensively used by local communities. About 400 plant species, mostly herbaceous endemics of high medicinal value, are harvested in the high elevation grasslands of Sikkim

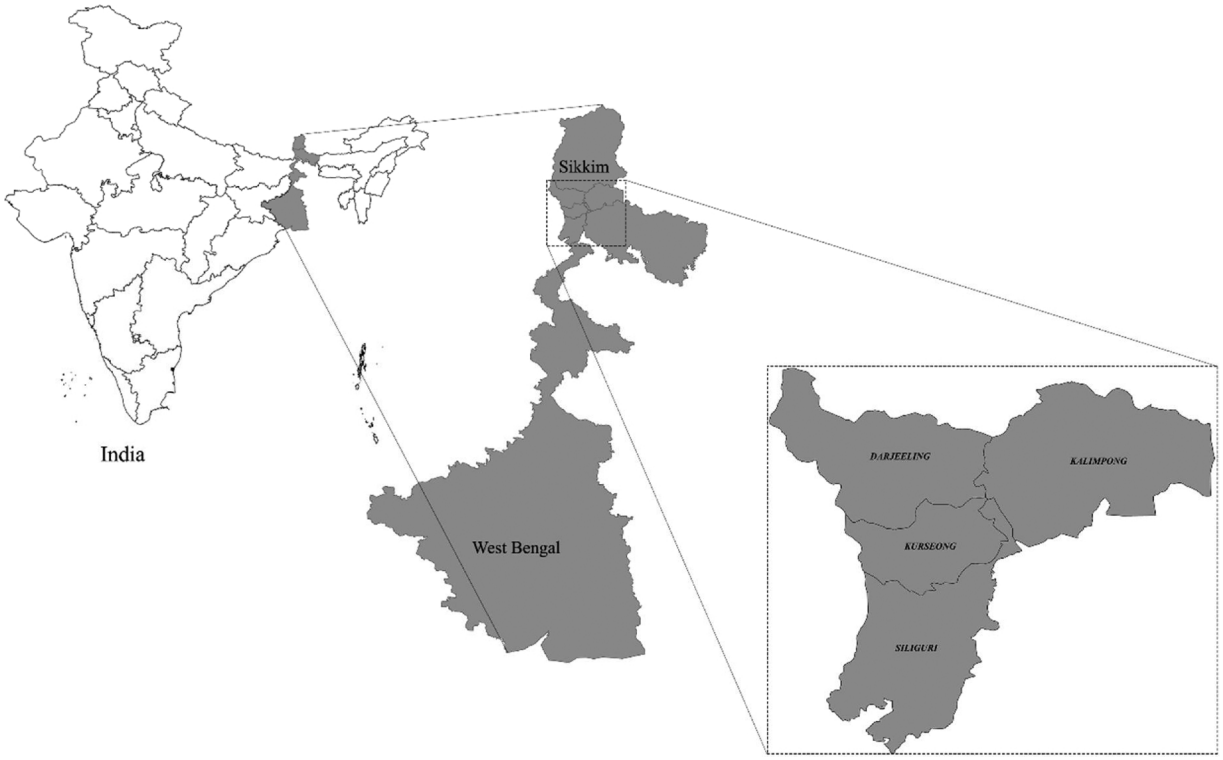

Fig. 1. The location of the study area in the Darjeeling region, Himalaya (bottom right), located in North-East India (top left), in West Bengal (center).

Himalaya (Rai et al., 2000). Eventual loss of endemic herbs would greatly affect the socio-economic structure of the community. Ecological alteration of the landscape and the associated changes in ecosystem structure and function following intrusion of *Yushania maling* will substantially impact local livelihoods. Replacement of conifers and important flora like Rhododendrons, Takus, Magnolia, Betula, Quercus etc. will affect timber supply and wildlife in the area.

2.2. Data collection: Yushania maling in the study area

Based on a 1 km^2 grid 56 locations were selected at which occurrence records of *Yushania maling* was collected. The surveys were carried out during the post monsoon period. Results were used for model parameter fitting.

2.3. Bioclimatic data and mapping

Current bioclimatic information at ~ 1 km^2 resolution is required to determine suitability of a specific area for *Yushania maling*. We derived 19 bioclimatic variables for the region from the World Climatic Research Centre (Hijmans et al., 2005) using Diva-GIS software (Appendix, Table 4). Additionally, land use cover was generated from LANDSAT satellite imagery obtained from USGS (https://www.usgs.gov). The land use land cover map (LULC) of the case study area was prepared using LANDSAT data from the year of the study. To assess mapping accuracy, Kappa coefficient (Smits et al., 1999); a discrete multivariate technique for assessment of mapping accuracy was used. The Kappa accuracy of the map was computed as 0.82. The geographic dimensions of environmental layers for the study area and pixel size was homogenised using the spatial analyst tool in ArcGIS ver. 10.1.

We reduced our full set of 23 environmental variables (Appendix, Table 4), to those with a significant impact by assessing their level of contribution to the final model using Maxent. Variables with higher maximum entropy gains were retained. Further exclusion of the variables was carried out by examining co-linearity. The results of this assessment can be found in the Appendix, (Table 5). Of each pair of highly cross-correlated variables (Pearson correlation coefficient $r > 0.90$), one was chosen considering its biological relevance to the species, and ease of interpretation for inclusion in the model (Kumar and Stohlgren, 2009). For example, if annual temperature and temperature seasonality were highly correlated, we kept temperature seasonality since it captured a seasonal variability in temperature. Ultimately, 5 significant environmental variables were selected for modelling potential habitat suitability of *Yushania maling* (Table 1). Table 2 illustrates the strength/contribution of each of the 5 selected variables for *Yushania maling* in describing their potential habitat suitability distribution. Max temperature of the warmest month was found to be the most significantly limiting factor for the species' distribution in the case study area.

2.4. Current species distribution models

For comparing model performance and to develop an ensemble prediction map for *Yushania maling* in our case study area we chose 3 current species distribution modelling tools:

1) BIOCLIM version 5.1 (Nix, 1986; Martin, 1996).
2) GARP, version 0.5 (Stockwell, 1999), and
3) Maxent, version 3.3.3e (Phillips et al., 2006; Phillips and Dudík,

Table 1
Selected environmental predictor variables for the use in the *Yushania maling* species distribution models, their native spatial resolution and data sources.

Predictor variables	Description	Native spatial resolution	Source
Climatic variables			
BIO3	Isothermality	1km	Worldclim
BIO5	Max temperature of warmest month	1km	Worldclim
BIO6	Min temp. coldest month	1km	Worldclim
BIO15	Precipitation seasonality	1km	Worldclim
BIO17	Precipitation driest quarter	1km	Worldclim

Table 2
Contribution of each of the 7 selected variables in Maxent model for *Yushania maling*.

Variable	Contribution [%]
Max Temperature of Warmest Month	78.1
Isothermality	15.4
Min Temperature of Coldest Month	3
Precipitation of Driest Quarter	2.5
Precipitation Seasonality	1

2008)

The chosen models are easy to use, batchable and have been providing regular robust estimates of predictions in various research (Wisz et al., 2008). Moreover, they do not need absence information to model the distribution. The models have proven to perform well with presence-only data and differ both conceptually as well as statistically (Elith et al., 2006; Kelly and Goulden, 2008). While the models GARP and BIOCLIM have been established well before Maxent, their underlying modelling approaches have shown to be less efficient in comparison (Elith et al., 2006). The SDMs represents the inherent relationship between species presence and a set of environmental conditions, but different SDM methods model this relationship differently, based on underlying principle. For e.g., BIOCLIM deals with this relationship as a binary predictor and broadly defined bioclimatic envelope, whereas Maxent and GARP include much complex nonlinear functions to model the relationship (Ju and Santos, 2012).

BIOCLIM was the first SDM to be developed for use by the wider public and laid the groundwork for most of the modelling tools existing today, including GARP and Maxent (Booth et al., 2013). The model interpolates a species' bioclimatic envelope - which is a summary of climatic conditions at locations where the species has been recorded (Hutchinson, 1982; Nix, 1986; Martin, 1996). BIOCLIM describes each species' bioclimatic envelope in a range based manner, suggesting that all locations with climatic parameters that fit within the extreme values determined at places of current species occurrences can be considered suitable habitat (Carpenter et al., 1993). BIOCLIM'S categorical output is mapped to probabilities of 1.0, 0.5 and 0.0 respectively.

GARP, the Genetic Algorithm for Rule-set Prediction, can find non-random correlations between the presence and absence of a species and environmental variables. It allows building species prediction models based on atomic, logistic regression, bioclimatic envelope and negated bioclimatic envelope rules and uses a super-algorithm in a dynamic machine-learning environment to do so (Payne and Stockwell, 1996; Stockwell and Peterson, 2002; Anderson et al., 2003). GARP works in an iterative process of rule selection, evaluation, testing and incorporating or rejecting to produce a heterogeneous rule set summarizing a species' ecological requirement (Anderson et al., 2002).

Maxent is the most current of the 3 tools, and its development was, in part, based on previously developed SDMs. Maxent is a software for modelling species niches and distribution by applying a machine-learning technique called maximum entropy modelling. From a set of environmental (e.g., climatic) grids and georeferenced occurrences, the model expresses a probability distribution where each grid cell has a predicted suitability of conditions for the species (Phillips et al., 2017). The software uses a generative approach, rather than discriminative, which can be an advantage when underlying data is limited. Additionally, it allows direct integration with GIS software such as ArcGIS, making data handling and mapping of model outputs easy.

2.5. Modelling comparison, ensemble modelling and future potential distribution prediction

In a first step we created current probability maps showing habitat suitability for *Yushania maling* with each of the 3 base modelling tools BIOCLIM, GARP and Maxent. We used 75% randomly assigned occurrences as training dataset with the remaining 25% used as test dataset.

For generating modelling output from BIOCLIM all values were kept at default levels in the modelling tool. Each model prediction was combined to represent composite prediction with an output pixel value ranging from 0 - 1. BIOCLIM outputs are categorical probability values of 0, 0.5 and 1.

To generate single binary predictions using GARP the Logit rule was applied using default parameters (0.01 convergence limit, and 1000 maximum iterations). Logit rules are an adaptation of logistic regression models, or a form of regression where outputs are transformed into probabilities (Stockwell, 1999).

The linear limiting feature functions which are equal to continuous environmental variables were used to train Maxent after realizing the small occurrence dataset and identifying appropriate feature shapes as suggested by Merow et al., (2013). Initially, the multiplier value was set to a very small value (e.g. 0.02) with a default set of parameters, leading to a highly over-fitted model. Subsequently, the multiplier value was increased and the modelled distribution and changes in AUC (area under curve, or area under the receiver operating characteristic (ROC) curve) was analyzed following an approach by Padalia et al., (2014). Jackknife resampling was used to identify those variables that contributed most to the model. The method provides a systematic method of resampling and leads to improved estimates of the sample parameter and a lower sampling bias (Tukey, 1958).

The logistic output of Maxent with habitat suitability values ranging from 0 (unsuitable) to 1 (optimal habitat) was recorded accordingly. Habitat suitability was classified as unsuitable (0–0.25), least suitable (0.25–0.50), moderately suitable (0.50–0.75) and highly suitable (0.75–1.00). For GARP and BIOCLIM habitat suitability was classified as unsuitable (< 0.5) and suitable (> 0.5).

In a second step we converted these habitat suitability maps into binary maps, showing potential habitat versus the area not suitable for the *Yushania maling*. This step was necessary to allow the comparison of outputs of all 3 models and the creation of an EM. For the conversion to binary maps we selected a threshold from our test data in which the specificity was equal to sensitivity following an approach described by Stohlgren et al., (2010).

Finally, we developed an EM based map for *Yushania maling* using a simple weighted summation approach for combining the 3 binary maps and then multiplying the resulting map by individual model performance following an approach described by Poulos et al., (2012). We chose the weighted summation approach due to its straightforward output that allows easy interpretation (Marmion et al., 2009). Ensemble scores in the modelled output represent the degree of model agreement. A pixel with a value of zero indicates that none of the models predicted species occurrence at a specific location. Larger values indicated a higher prediction agreement among the 3 models, which suggested that these locations were robustly estimated to be suitable habitat.

In a third step we projected the trained Maxent model into future climates (HadCM3 A2a and B2a) scenarios using projection feature utility in Maxent following Padalia et al., (2015). We retained the same thresholding criteria as discussed above in current Maxent model in order to categorize into likewise occurrence probabilities.

Model accuracy was assessed using the threshold independent receiver operating characteristic (ROC) AUC method. AUC is widely used for comparing species distribution model performance, or statistical model performance in general. The ROC curve is defined by plotting sensitivity against '1 minus specificity' across the range of possible thresholds. Sensitivity and specificity are used to take into account all elements of a confusion matrix (true and false presences and absences). The ROC curve describes the relationship between the proportion of observed presences correctly predicted (sensitivity) and the proportion of observed absences incorrectly predicted (1 minus specificity). A high AUC score reflects that the model can discriminate accurately between locations at which the species is present or absent. The AUC measures

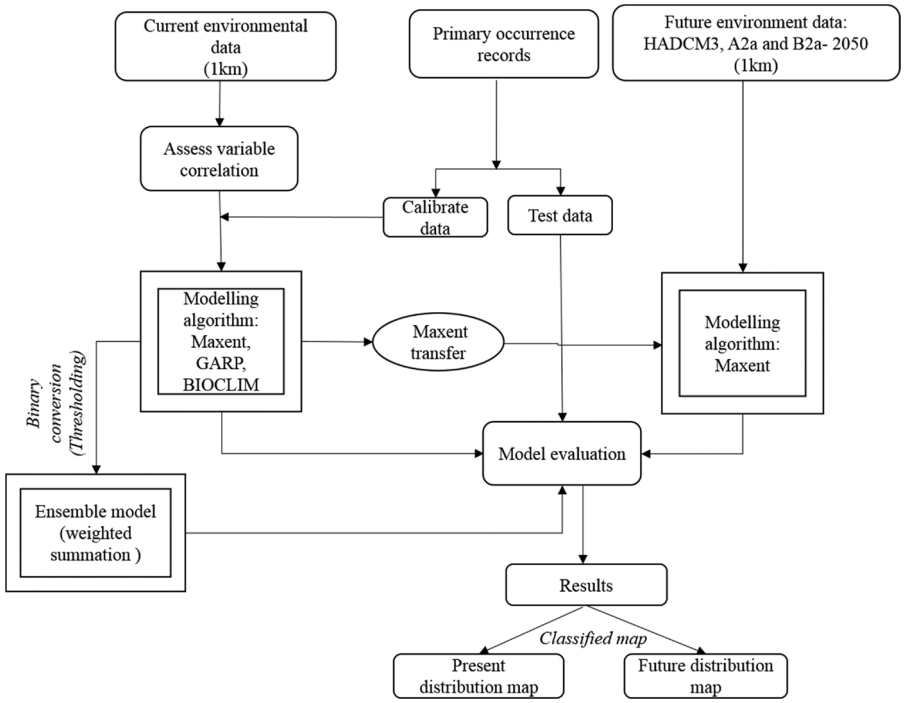

Fig. 2. Flowchart showing the structured data processing and modelling approach used for this study.

model performance that ranges from 0 to 1. A model performs well when the AUC is large. Usually, AUC values of > 0.9 indicate high accuracy, values of 0.70-0.9 indicate good accuracy, and values between 0.5 and 0.7 indicate low accuracy.

For our model AUC values were calculated using a web-based calculator for ROC curves (Eng, 2006). We generated 100 pseudo absence points using ArcMap by randomly generating points using a 100-km buffer around species presence records following Poulos et al., (2012). Fig. 2, displays the overall structure of the modelling approach.

3. Results

3.1. Prediction of potential distribution

Model performances of Maxent, GARP and BIOCLIM were not similar to that of EM. The overall area of suitable habitat calculated using Maxent, GARP, BIOCLIM and EM were 1853 km^2, 2881 km^2, 2703 km^2 and 2972 km^2 respectively. Moreover, spatial uncertainties also could not entirely be eliminated: The modelling results obtained using Maxent showed potential habitat for *Yushania maling* in Darjeeling Phulbazar, Jourbunglow, Sukiapokhri, Rangli Rangliot, Kalimpong, parts of Darjeeling district and adjoining areas of Nepal, Bhutan and Sikkim (Fig. 3), while the results obtained using GARP identified areas of suitable habitat in Kalimpong, Gorubathan, Bhutan, Mirik, Jourbungalow and Sukiapokhri that are overall larger than those derived using Maxent and BIOCLIM. Furthermore, results obtained using BIOCLIM showed an increased area suitability in Sikkim and Mirik compared to results obtained using other models.

Field data and modelling outputs indicate that areas experiencing maximum temperatures between 12.4–20 °C in the warmest months (Fig. 4) and elevations of 1300 to 3,400 m above mean sea level (mamsl) are suitable for *Yushania maling*. Suitable habitat for *Yushania maling* was identified as up to a maximum elevation of 3400 mamsl in Nepal, adjoining to Darjeeling district, as well as at 2800 mamsl towards Bhutan. This modelled suitable region is also the maximum species richness zone (1500–2500 mamsl) (Vetaas and Grytnes, 2002).

Although the predictive capacity of individual models differed, as for example shown in AUC scores, area predicted to be suitable habitat matched with species' ecology and field survey data in all cases except for GARP, which was found to over predict habitat suitability outside of the IAS' known ecological niche. Moderately and highly suitable habitat (> 0.5 probability) for *Yushania maling* predicted by models correlated well with occurrence records from field sampling (Table 3).

The jackknife test identified max. temperature of warmest month and min. temperature of coldest month (Fig. 5) as the most important environmental variables for predicting potential habitat suitability of *Yushania maling* in the study area.

Of the four modelling algorithms EM and Maxent did perform best with AUC values 0.95 and 0.94 respectively. GARP and BIOCLIM ranked the lowest with AUCs of 0.82 and 0.71. While AUC values were marginally different between EM and Maxent, our results suggest that EM has a higher accuracy compared to results individually derived using GARP or BIOCLIM. Maxent predictions and high ensemble scores were well in accordance with the presence records of *Y. maling*.

3.2. Impact of climate change

Fig. 6 shows the potential range of *Yushania maling* habitat modelled for the year 2050 under A2a and B2a climate change scenarios. The results show that the *Yushania maling* distribution area in A2a scenario remains relatively similar to its current distribution with 1853 km^2 and 1883 km^2 respectively. However, a transition is observed from moderately suitable areas to highly suitable in areas close to Bhutan and in the north of Darjeeling. For scenario B2a the total area suitable for *Y. maling* was smaller (1840 km^2) than that obtained under current climatic conditions and the A2a scenario. The highly suitable areas (> 0.75 probability) decreased from 260 km^2 or 2.95% in A2a scenario to 245 km^2 or 2.78% in size in the B2a scenario.

4. Discussion & conclusions

Today various methods exist to assess potential habitat but only few studies directly compare their explanatory power, specifically with IAS is question. In this study we visualized the differences between all three models, from the simplest (BIOCLIM) to the most advanced (Maxent). We eliminated each model's potential drawbacks by adopting an

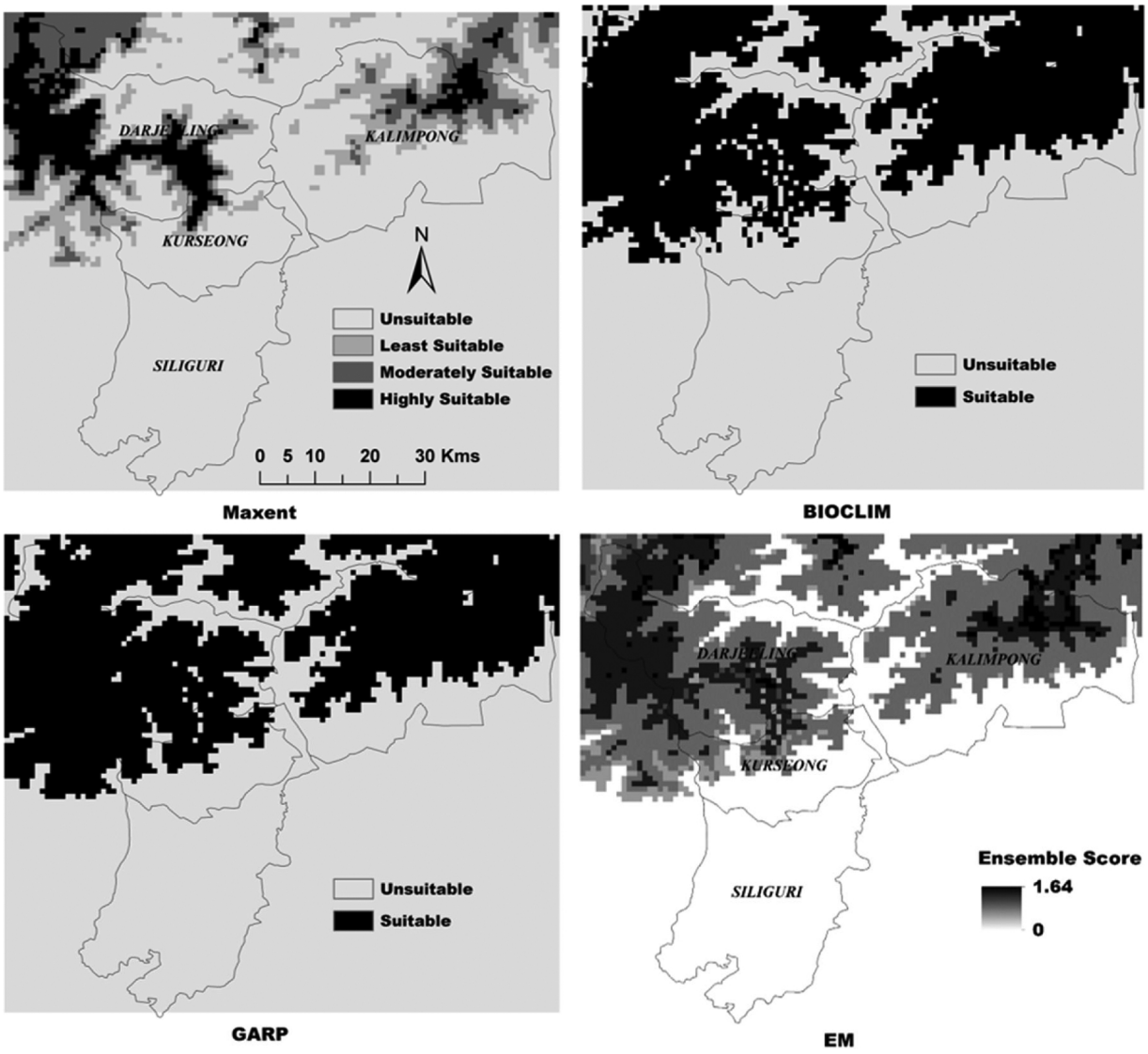

Fig. 3. Potential distribution maps for *Yushania maling* modelled using Maxent, BIOCLIM, GARP and EM. EM values were calculated using a weighted summation approach where each model was weighted by its performance and a resulting sum was formed. Values range from 0 to 1.64.

ensemble approach. While, GARP and BIOCLIM performed consistent, Maxent and EM did outperform them. Even though our EM had the highest AUC score for invasive *Yushania maling*, Maxent did perform insignificantly lower. Accordingly, our study revealed major variations in the area suitable for *Yushania maling* derived using the selected modelling approaches. Therefore, our first hypothesis *"$H_{0,1}$: Model performance of Maxent, GARP and BIOCLIM is similar to that of EM when using field data for Yushania maling."* was rejected. Our results generally support the use of EM over individual SDMs, however, EM does not always outperform all other models. In this case, the individual Maxent model delivered more accurate results. Nonetheless, EM can provide more realistic simulations of species spread and distribution because of the fact that they highlight the mutual areas of agreement among the individual models (Araujo and New, 2007; Marmion et al., 2009) and further can accommodate wide arrange of algorithms. So, a decision to perform ensemble modelling with three well established SDM approaches can based on the following grounds: (a) BIOCLIM is one of the oldest known SDMs and is widely used in different studies by a wide range of authors (e.g. Cunningham et al., 2002; Steinbauer et al., 2008; Loiselle et al., 2003; Meynecke, 2004; Walther et al., 2004), but the method was criticised for the inclusion of unnecessary parameters leading to omissions errors i.e., areas being classified as climatically unsuitable while the IAS was in fact able to get established there (Kriticos and Randall, 2001; Chilcott et al., 2003; Williams et al., 2003). (b) GARP has an excellent predictive ability and is insensitive to BIOCLIM's challenges with dimensionality of environmental data (Peterson and Cohoon, 1999) but both approaches tend to over predict habitat (Peterson, 2001; Padalia et al., 2014). (c) The accuracy of GARP models has been analyzed generally for species whose distributions are already known (e.g. Anderson et al., 2002, 2003, e.g., Peterson, 2003; Loiselle et al., 2003). Furthermore, there is no significant differences in model accuracy between GARP and BIOCLIM (Elith et al., 2006; Loiselle et al., 2003).

All models did show significant differences in spatial habitat predictions, reflecting the inherent inter-model uncertainty, suggesting that predictive power significantly varies depending on the statistical algorithms used as also shown in a study by Elith et al., (2006). Uncertainties exist in all statistical models (Phillips et al., 2006, 2009) however, including weak base models in an EM can weaken overall results (Stohlgren et al., 2010). We therefore included only SDMs with an AUC of 0.7 or above. While some knowledge of model performance is required to choose the ones to combine in ensemble modelling we considered the most commonly used models for our dataset. To aid choosing from a wider range of models in the future, a pairwise

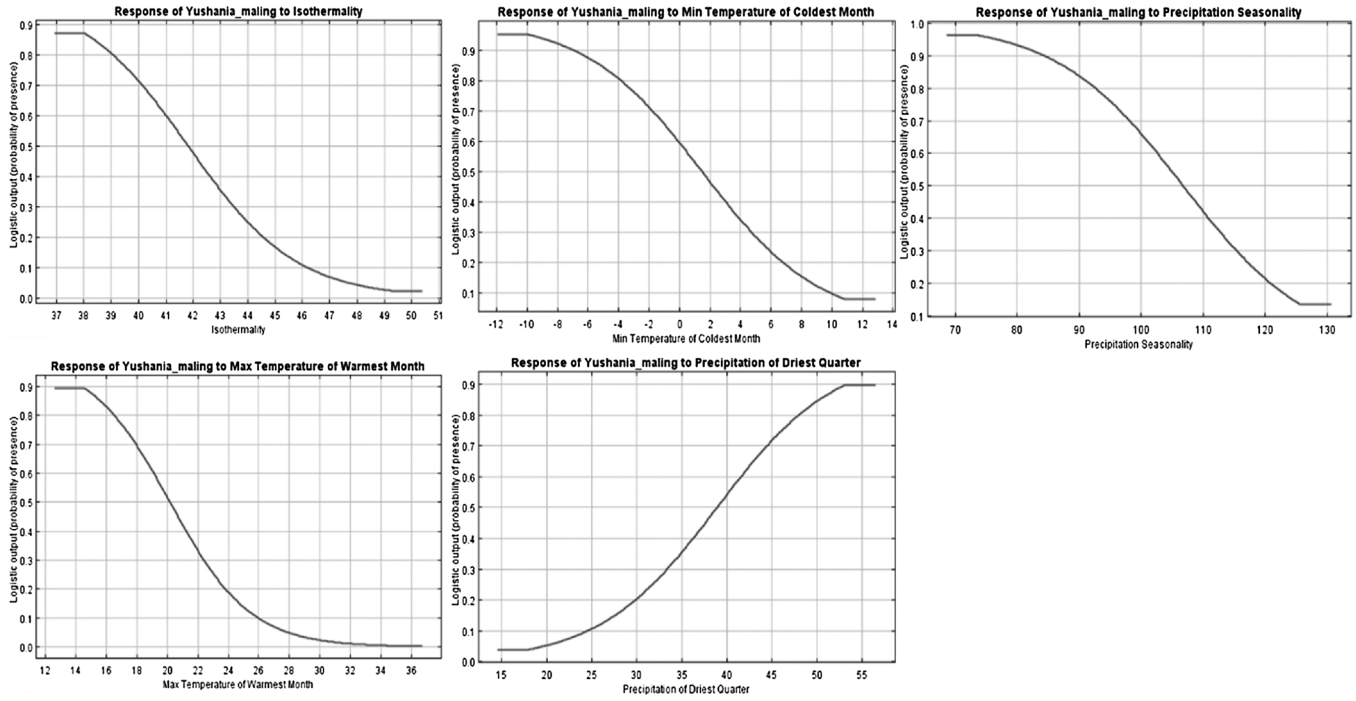
Response of Yushania_maling to Isothermality
Logistic output (probability of presence)
Isothermality
Response of Yushania_maling to Min Temperature of Coldest Month
Min Temperature of Coldest Month
Response of Yushania_maling to Precipitation Seasonality
Precipitation Seasonality
Response of Yushania_maling to Max Temperature of Warmest Month
Max Temperature of Warmest Month
Response of Yushania_maling to Precipitation of Driest Quarter
Precipitation of Driest Quarter

Fig. 4. Relationships between environmental predictor variables and the probability of presence of *Yushania maling* in Darjeeling, Himalaya.

Table 3
Model predicted probability values of occurrence of *Yushania maling* in different models.

Geographic position	Model predicted probability values of *Y. maling* presence				Ground observation
	Maxent score	GARP	BIOCLIM	Ensemble	
27.13N, 88.74E	0.80	1	0.5	1.37	Present-Suitable area
26.99N, 88.28E	0.79	1	0.5	1.36	Present-Suitable area
27.00N, 88.21E	0.76	1	0.5	1.35	Present-Suitable area
26.98N, 88.15E	0.80	1	0.5	1.37	Present-Suitable area
26.98N, 88.13E	0.77	1	0.5	1.35	Present-Suitable area
27.00N, 88.03E	0.67	1	1	1.30	Present-Suitable area
26.18N, 88.11E	0.05	1	0	0.60	Absent-Not suitable
26.87N, 88.30E	0.27	1	0	0.72	Absent-Not suitable
26.94N, 88.47E	0.01	1	0	0.58	Absent-Not suitable
27.01N, 88.49E	0.01	1	0	0.58	Absent-Not suitable

comparison of high performing algorithms could be considered. Our results show that EM performed equally good as Maxent, which is in line with the findings from studies carried out by Stohlgren et al., (2010) and Poulos et al., (2012). However, in our case, performance differences between Maxent and EM were minimal and do not necessarily justify the extra work required to build an EM. Selection of models do greatly influence the results. Though we tested the high performing models but still there are no previous related comparison studies using the same set of SDMs for EM. Our results might be affected by sampling bias, non availability of absence data and individual model variances. Moreover, we didn't calculated confidence intervals for our predictions. So similar advance studies in the future would validate our choice of EM. Furthermore, IAS habitat cannot entirely be defined by bioclimatic variables alone. Hence, we suggest that future studies also address the effects of human induced spread.

We combined *Yushania maling* habitat forecasts using the simple weighted summation approach as it offers a simple and straightforward way to unite various species distribution models and its output is easy to interpret. Our EM produced good spatial correlation between potential habitat and actual presence, relative to single-algorithm predictions. However, the way in which individual model outputs are combined also affects the EM results. Various ensemble methods are now available, but one based on average function algorithms is likely to increase the accuracy of species distribution forecasts, and thus exhibiting substantial potential for numerous conservation applications (Marmion et al., 2009). To fully understand the reasons for EM behaviour and results a wider study is required that addresses which aspects of EM have the biggest impact on species distribution forecasts.

Our modelling output shows that temperate conifer and broad-leaved mixed forests are a preferred habitat for *Y. maling*, which in turn

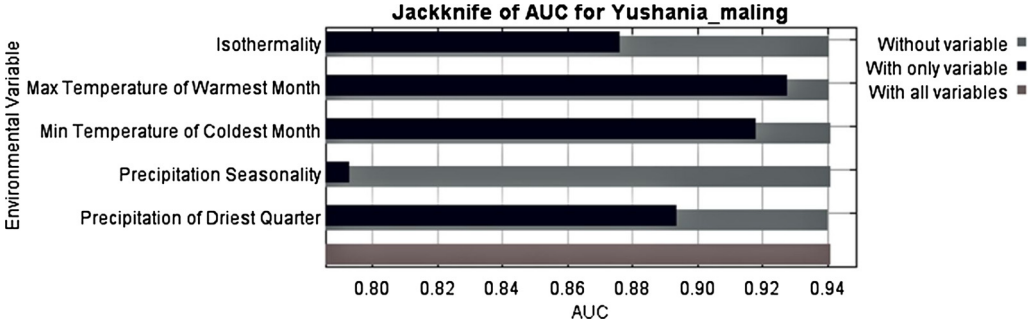

Fig. 5. Results of Jackknife test showing the influence (AUC) of each individual environmental variable relative to all environment variables in the Maxent model.

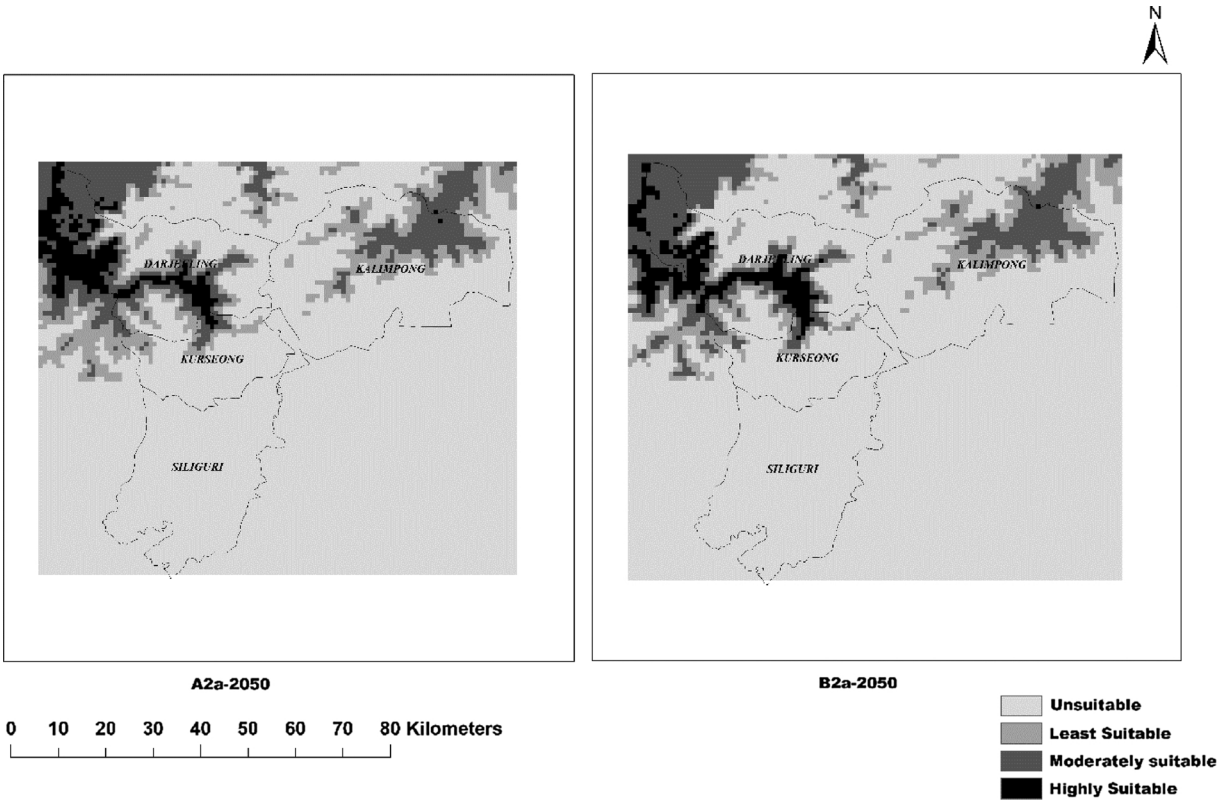

Fig. 6. Potential habitat suitability of *Yushania maling* modelled for the year 2050 under A2a and B2a climate change scenarios.

leads to the outcome that protected areas like Singallila NP, Barsay WLS, Neora valley NP and Senchal WLS - some of which are currently unaffected buy the species - offer highly suitable habitat for the species. This indicates a specifically high threat given the ecological relevance of these protected areas. Accordingly, and not surprisingly, we are therefore able to also reject our second hypothesis "$H_{0,2}$: The spread of *Yushania maling* is limited. No currently unaffected areas in the region are at risk of being invaded". The invasion potential of *Yushania maling* in Darjeeling Himalayas has reached alarming levels and is a great concern for policy makers in the region (Roy et al., 2016). However, there is lack of scientific information available regarding the management of invasive *Y. maling*. While digging up and or repeatedly cutting bamboo plants appears to be the most successful countermeasure as reported by locals, a better knowledge of habitat requirements will allow to ensure that the most sensitive areas are prioritized. The distribution maps produced from this study will assist policy- and decision makers to ensure all efforts to have the highest effectiveness.

Overall, our findings are in line with those presented by Roy et al., (2016). The authors used a Graph theoretic network approach and Maxent to model the potential connectivity of invasive species through natural areas and map their potential distribution. The authors found that the forested regions of Singalilla NP, Senchal WLS and Neora Valley NP were the key vertices for the spread of *Y. maling,* a finding that is in line with the results reported in this study. However, the authors, modelled *Y. maling* suitability at elevations between 3600 and 1600 mamsl, while we considered a wider range (3400–1300 mamsl), when running Maxent separately with additional elevation information (Table 4). Using a wider elevation range was made possible by using different input predictor variables, as well as model fitting and calibration techniques. Still, both studies identified temperate conifer and broad-leaved mixed forests as *Y. maling*'s preferred habitat, with the study at hand providing additional insight on the variation in spatial prediction patterns.

Our results of climate change impacts on the distributions of invasive *Y. maling* show that in the A2a scenario (higher rate of population growth and energy use) the area suitable for the species increases by~ 30 km^2. Locations near Bhutan and north of Darjeeling will provide suitable habitat for a successful invasion. In difference to that, when applying scenario B2a (lower rate of population growth and energy use) the suitable area decreased to 13 km^2 when compared to the current potential distribution of 1853 km^2. Thus, we reject our third hypothesis "$H_{0,3}$: There is no difference in the potential habitat of *Yushania maling* under a changing climate". North-West regions of Darjeeling Himalayas and regions of Bhutan were found to be more uncertain with respect to habitat suitability in both the scenarios. This might be due to high elevation changes in the region. However, we found that the overall spatial pattern of habitat distributions of *Y. maling* remains very similar to its present distribution, a finding that will greatly help in formulating long term conservation and eradication plans.

Climate change is inevitable, and the Himalayas are warming at much higher rates than the global average of 0.74 C over the last 100 years (Kumar, 2012). Kumar (2012) found that the higher elevations in the north of Sikkim Himalaya to be particularly affected by changes in climate with an 18% loss of endemic species. Based on our projections under scenario A2a, and recent reports of increased anthropogenic pressure in the region such as intense hydropower development (Pandit and Grumbine, 2012; Grumbine and Pandit, 2013), combined with ongoing deforestation (Pandit et al., 2006), urbanization and tourism (Grumbine and Pandit, 2013) challenges in the region are likely to increase. Accordingly, studies like the one at hand are of increasing relevance when it comes to directing mitigation efforts.

Finally, we advocate that EM must be created using well trained individual models, pertaining to idea that the better the individual forecast, the better the resulting EM will be. Resource managers should aim to use EM over individual models to fully harness its potential to provide more realistic species distribution simulations, a step that will - with the advancement of technology - will become increasingly easy.

Acknowledgements

This work has been carried out within the framework of the project "Vulnerability assessment of Darjeeling Himalaya to climate change". The work was generously funded by the West Bengal Biodiversity Board, Kolkata, West Bengal, India.

The authors wish to thank Deepak Kushwaha and Sivi Mor for their advice on modelling and species identification; and the anonymous reviewers for valuable suggestions.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolmodel.2018.07.001.

References

Anderson, R.P., Gomez-Laverde, M., Peterson, A.T., 2002. Geographical distributions of spiny pocket mice in South America: insights from predictive models. Glob. Ecol. Biogeogr. 11 (2), 131–141. https://doi.org/10.1046/j.1466-822x.2002.00275.x.

Anderson, R.P., Lew, D., Peterson, A., 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. Ecol. Modell. 162 (3), 211–232. https://doi.org/10.1016/s0304-3800(02)00349-6.

Araujo, M., New, M., 2007. Ensemble forecasting of species distributions. Trends Ecol. Evol. 22 (1), 42–47. https://doi.org/10.1016/j.tree.2006.09.010.

Booth, T.H., Nix, H.A., Busby, J.R., Hutchinson, M.F., 2013. Bioclim: the first species distribution modelling package, its early applications and relevance to most current Maxent studies. Divers. Distrib. 20 (1), 1–9. https://doi.org/10.1111/ddi.12144.

Breiner, F.T., Guisan, A., Bergamini, A., Nobis, M.P., 2015. Overcoming Limitations of Modelling Rare Species by Using Ensembles of Small Models. pp. 1210–1218. https://doi.org/10.1111/2041-210X.12403.

Breiner, F., Bergamini, A., Nobis, M., Guisan, A., 2016. Optimising ensemble of small models (ESM) for modelling rare species in conservation practice. ESM - A New Modelling Strategy for Conservation Practice, vol. 2015. pp. 12403. https://doi.org/10.1111/2041-210X.12403.leave.

Carpenter, G., Gillison, A.N., Winter, J., 1993. DOMAIN: a flexible modelling procedure for mapping potential distributions of plants and animals. Biodivers. Conserv. 2 (6), 667–680. https://doi.org/10.1007/bf00051966.

Chilcott, C., Hilbert, D., Howden, M., 2003. Modelling biodiversity and climate change. In: Climate Change Impacts on Biodiversity in Australia: Outcomes of a Workshop Sponsored by the Biological Diversity Advisory Committee. Environment Australia, Canberra. pp. 63–66.

Chi-Son, C., Renvoize, S.A., 1989. A revision of the species described under arundinaria (gramineae) in Southeast Asia and Africa. Kew Bulletin 44 (2), 349. https://doi.org/10.2307/4110809.

Di Cola, V., Broennimann, O., Petitpierre, B., Breiner, F.T., Amen, M.D., Randin, C., et al., 2017. ecospat : an R package to support spatial analyses and modeling of species niches and distributions. November 2016. pp. 774–787. https://doi.org/10.1111/ecog.02671.

Comte, L., 2013. Species distribution modelling and imperfect detection: comparing occupancy versus consensus methods. Divers. Distrib. 996–1007. https://doi.org/10.1111/ddi.12078.

Cunningham, D.C., Anderson, E.R., Walsh, K.B., 2002. Ecology and biogeography of Cassia brewsteri: assessment of potential sites for cultivation. Aust. J. Exp. Agric. 42 (8), 1071. https://doi.org/10.1071/ea02022.

Elith, J., Graham, C.H., Anderson, R.P., Dudík, M., Ferrier, S., Guisan, A., et al., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29 (2), 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x.

Elton, C.S., 1958. The Ecology of Invasions by Animals and Plants. https://doi.org/10.1007/978-1-4899-7214-9.

(Eng J. ROC analysis: web-based calculator for ROC curves. Baltimore: Johns Hopkins University [updated 2014 March 19; cited]. Available from: http://www.jrocfit.org).

Forester, B.R., Dechaine, E.G., Bunn, A.G., 2013. Distributions. pp. 1480–1495. https://doi.org/10.1111/ddi.12098.

Gillard, M., Thie, G., Boris, D., 2017. Present and future distribution of three aquatic plants taxa across the world : decrease in native and increase in invasive ranges. Biol. Invasions. https://doi.org/10.1007/s10530-017-1428-y.

Grumbine, R.E., Pandit, M.K., 2013. Threats from India's Himalaya dams. Science 339 (6115), 36–37. https://doi.org/10.1126/science.1227211.

Guisan, A., Thuiller, W., 2005. Predicting Species Distribution: Offering More than Simple Habitat Models. Retrieved May 10, 2017, from. https://doi.org/10.1111/j.1461-0248.2005.00792.x/abstract.

Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecol. Modell. 135 (June 2-3), 147–186. https://doi.org/10.1016/s0304-3800(00)00354-9.

Hadley, K.S., 1987. Vascular alpine plant distributions within the Central and Southern Rocky mountains. U.S.A. Arctic and Alpine Research 19 (3), 242. https://doi.org/10.2307/1551359.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25 (15), 1965–1978. https://doi.org/10.1002/joc.1276.

Hobbs, R.J., 2000. Land-Use Changes and Invasions. Invasive Species in A Changing World. pp. 55–64.

Hutchinson, M., 1982. MAPROJ — a computer map projection system. Cartography 12 (3), 144–145. https://doi.org/10.1080/00690805.1982.10438185.

Jiménez-Valverde, A., Peterson, A.T., Soberón, J., Overton, J.M., Aragón, P., Lobo, J.M., 2011. Use of niche models in invasive species risk assessments. Biol. Invasions 13 (12), 2785–2797. https://doi.org/10.1007/s10530-011-9963-4.

Ju, P.D.M., Santos, T., 2012. Study with Jaguars in the Neotropics. pp. 615–627. https://doi.org/10.1111/j.1472-4642.2012.00892.x.

Kelly, A.E., Goulden, M.L., 2008. Rapid shifts in plant distribution with recent climate change. Proc. Natl. Acad. Sci. 105 (33), 11823–11826. https://doi.org/10.1073/pnas.0802891105.

Körner, C., 1999. The alpine life zone. Alpine Plant Life 9–19. https://doi.org/10.1007/978-3-642-98018-3_2.

Kriticos, D.J., Randall, R.P., 2001. A comparison of systems to analyse potential weed distributions. Weed Risk Assess. 61–79.

Kumar, P., 2012. Assessment of impact of climate change on Rhododendrons in Sikkim Himalayas using Maxent modelling: limitations and challenges. Biodivers. Conserv. 21 (5), 1251–1266. https://doi.org/10.1007/s10531-012-0279-1.

Kumar, S., Stohlgren, T.J., 2009. Maxent modeling for predicting suitable habitat for threatened and endangered tree Canacomyrica monticola in New Caledonia. J. Ecol. Nat. Environ. 1 (4), 94–98.

Loiselle, B.A., Howell, C.A., Graham, C.H., Goerck, J.M., Brooks, T., Smith, K.G., Williams, P.H., 2003. Avoiding pitfalls of using species distribution models in conservation planning. Conserv. Biol. 17 (6), 1591–1600.

Mack, R.N., Simberloff, D., Mark Lonsdale, W., Evans, H., Clout, M., Bazzaz, F.A., 2000. Biotic invasions: causes, epidemiology, global consequences, and control. Ecol. Appl. 10 (3), 689–710.

Majumdar, R.B., et al., 1989. In: Karthikeyan, S. (Ed.), Flora Indicae, Enumeratio Monocotyledonae. Botanical Survey of India, Howrah, Calcutta, pp. 274–283.

Mark, A.F., Adams, N.M., 1973. New Zealand Alpine Plants. A. H. & A. W. Reed, Wellington.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. Divers. Distrib. 15 (1), 59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x.

Martin, W., 1996. The current and potential distribution of the common Myna Acridotheres tristisin Australia. Emu 96 (3), 166. https://doi.org/10.1071/mu9960166.

Meller, L., Cabeza, M., Pironon, S., Barbet-Massin, M., Maiorano, L., Georges, D., Thuiller, W., 2014. Ensemble distribution models in conservation prioritization: from consensus predictions to consensus reserve networks. Divers. Distrib. 20 (3), 309–321. https://doi.org/10.1111/ddi.12162.

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36 (10), 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x.

Meynecke, J., 2004. Effects of global climate change on geographic distributions of vertebrates in North Queensland. Ecol. Modell. 174 (4), 347–357. https://doi.org/10.1016/j.ecolmodel.2003.07.012.

Mooney, H.A., Drake, J.A., 1987. The ecology of: biological invasions. Environ. Sci. Policy Sustain. Dev. 29 (5), 10–37. https://doi.org/10.1080/00139157.1987.9928888.

Naimi, B., Araújo, M.B., 2016. Sdm: a reproducible and extensible R platform for species distribution modelling. Ecography 39 (4). https://doi.org/10.1111/ecog.01881.

Nix, H.A., 1986. A biogeographic analysis of Australian elapid snakes. Atlas of Elapid Snakes of Australia, vol. 7. pp. 4–15.

Ozenda, P., 1995. L'endémisme au niveau de l'ensemble du système alpin. Acta Bot. Gallica 142 (7), 753–762. https://doi.org/10.1080/12538078.1995.10515302.

Padalia, H., Srivastava, V., Kushwaha, S., 2014. Modeling potential invasion range of alien invasive species, Hyptis suaveolens (L.) Poit. in India: comparison of Maxent and GARP. Ecol. Inf. 22, 36–43. https://doi.org/10.1016/j.ecoinf.2014.04.002.

Padalia, H., Srivastava, V., Kushwaha, S.P., 2015. How climate change might influence the potential distribution of weed, bushmint (Hyptis suaveolens)? Environ. Monit. Assess. 187 (4). https://doi.org/10.1007/s10661-015-4415-8.

Pandit, M.K., Grumbine, R.E., 2012. Potential effects of ongoing and proposed hydropower development on terrestrial biological diversity in the Indian Himalaya. Conserv. Biol. 26 (6), 1061–1071. https://doi.org/10.1111/j.1523-1739.2012.01918.x.

Pandit, M.K., Sodhi, N.S., Koh, L.P., Bhaskar, A., Brook, B.W., 2006. Unreported yet massive deforestation driving loss of endemic biodiversity in Indian Himalaya. Biodivers. Conserv. 16 (1), 153–163. https://doi.org/10.1007/s10531-006-9038-5.

Payne, K., Stockwell, D.R.B., 1996. GARP Modelling System User's Guide and Technical Reference. Retrieved May 10, 2017, from. https://landshape.wordpress.com/2006/10/05/garp-modelling-system-users-guide-and-technical-reference/.

Peterson, A.T., 2001. Predicting species' geographic distributions based on ecological niche modeling. Condor 103 (3), 599. https://doi.org/10.1650/0010-5422(2001)103[0599:psgdbo]2.0.co;2.

Peterson, A., 2003. Predicting the geography of species' invasions via ecological niche modeling. Q. Rev. Biol. 78 (4), 419–433. https://doi.org/10.1086/378926.

Peterson, A.T., Cohoon, K.P., 1999. Sensitivity of distributional prediction algorithms to geographic data completeness. Ecol. Modell. 117 (1), 159–164. https://doi.org/10.1016/s0304-3800(99)00023-x.

Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with maxent: new extensions and a comprehensive evaluation. Ecography 31 (2), 161–175. https://doi.org/10.1111/j.0906-7590.2008.5203.x.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species

geographic distributions. Ecol. Modell. 190 (3-4), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.
Phillips, S.J., Dudík, M., Elith, J., Graham, C.H., Lehmann, A., Leathwick, J., Ferrier, S., 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecol. Appl. 19 (1), 181–197. https://doi.org/10.1890/07-2153.1.
Phillips, S.J., Anderson, R.P., Dudík, M., Schapire, R.E., Blair, M.E., 2017. Opening the black box: an open-source release of Maxent. Ecography. https://doi.org/10.1111/ecog.03049.
Poulos, H.M., Chernoff, B., Fuller, P.L., Butman, D., 2012. Ensemble forecasting of potential habitat for three invasive fishes. Aquat. Invasions 7 (1), 59–72. https://doi.org/10.3391/ai.2012.7.1.007.
Rai, L., Prasad, P., Sharma, E., 2000. Conservation threats to some important medicinal plants of the Sikkim Himalaya. Biol. Conserv. 93 (1), 27–33. https://doi.org/10.1016/s0006-3207(99)00116-0.
Roy, A., Bhattacharya, S., Ramprakash, M., Senthil Kumar, A., 2016. Modelling critical patches of connectivity for invasive Maling bamboo (Yushania maling) in Darjeeling Himalayas using graph theoretic approach. Ecol. Modell. 329, 77–85. https://doi.org/10.1016/j.ecolmodel.2016.02.016.
Scott, J.M., 2002. Predicting Species Occurrences: Issues of Accuracy and Scale. Island Press, Washington.
Sekar, K.C., 2012. Invasive alien plants of Indian Himalayan region—diversity and implication. Am. J. Plant Sci. 03 (02), 177–184. https://doi.org/10.4236/ajps.2012.32021.
Smits, P.C., Dellepiane, S.G., Schowengerdt, R.A., 1999. Quality assessment of image classification algorithms for land-cover mapping: a review and a proposal for a cost-based approach. Int. J. Remote Sens. 20 (8), 1461–1486. https://doi.org/10.1080/014311699212560.
Stapleton, C.M.A., 1997. The morphology of woody bamboos. Linnean Society Symposium Series 19. Academic Press Limited, pp. 251–268.
Steinbauer, M.J., Yonow, T., Reid, I.A., Cant, R., 2008. Ecological biogeography of species of Gelonus, Acantholybas and Amorbus in Australia. Aust. Ecol. 27 (1), 1–25. https://doi.org/10.1111/j.1442-9993.2002.tb00149.x.
Stockwell, D., 1999. The GARP modelling system: problems and solutions to automated spatial prediction. Int. J. Geogr. Inf. Sci. 13 (2), 143–158. https://doi.org/10.1080/136588199241391.
Stockwell, D.R., Peterson, A., 2002. Effects of sample size on accuracy of species distribution models. Ecol. Modell. 148 (1), 1–13. https://doi.org/10.1016/s0304-3800(01)00388-x.
Stohlgren, T.J., Ma, P., Kumar, S., Rocca, M., Morisette, J.T., Jarnevich, C.S., Benson, N., 2010. Ensemble habitat mapping of invasive plant species. Risk Anal. 30 (2), 224–235. https://doi.org/10.1111/j.1539-6924.2009.01343.x.
Thuiller, A.W., Georges, D., Engler, R., Georges, M.D., Thuiller, C.W., 2016. The biomod2 Package: the Updated Object-Oriented Version of BIOMOD Package 2. pp. 1–104. Retrieved from. https://cran.r-project.org/web/packages/biomod2/index.html.
Tukey, J.W., 1958. A smooth invertibility theorem. Ann. Math. Stat. 29 (2), 581–584. https://doi.org/10.1214/aoms/1177706635.
Vetaas, O.R., Grytnes, J., 2002. Distribution of vascular plant species richness and endemic richness along the Himalayan elevation gradient in Nepal. Global Ecol. Biogeogr. 11 (4), 291–301. https://doi.org/10.1046/j.1466-822x.2002.00297.x.
Walther, B.A., Wisz, M.S., Rahbek, C., 2004. Known and predicted African winter distributions and habitat use of the endangered Basra reed warbler (Acrocephalus griseldis) and the near-threatened cinereous bunting (Emberiza cineracea). J. Ornithol. 145 (4), 287–299. https://doi.org/10.1007/s10336-004-0036-7.
Williams, S.E., Bolitho, E.E., Fox, S., 2003. Climate change in Australian tropical rainforests: an impending environmental catastrophe. Proc. R. Soc. B: Biol. Sci. 270 (1527), 1887–1892. https://doi.org/10.1098/rspb.2003.2464.
Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham, C.H., Guisan, A., 2008. Effects of Sample Size on the Performance of Species Distribution Models. pp. 763–773. https://doi.org/10.1111/j.1472-4642.2008.00482.x.